## Deep Convolutional Neural Networks for Spatiotemporal Crime Prediction

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Abstract - Crime, as a long-term global problem, has been showing the complex interactions with space, time and environments. Extracting effective features to reveal such entangled relationships to predict where and when crimes will occur, is becoming a hot topic and also a bottleneck for researchers. We, therefore, proposed a novel Spatiotemporal Crime Network (STCN), in an attempt to apply deep Convolutional Neural Networks (CNNs) for automatically crime-referenced feature extraction. This model can forecast the crime risk of each region in the urban area for the next day from the retrospective volume of high-dimension data. We evaluated the STCN using felony and 311 datasets in New York City from 2010 to 2015. The results showed STCN achieved 88% and 92% on F1 and AUC respectively, confirming the performances of STCN exceeded those of four baselines. Finally, the predicted results was visualized to help people understanding its linking with the ground truth.

**Keywords:** Crime Spatiotemporal Prediction; Crime Risk Estimation; CNN (Convolution Neural Networks); Deep Learning; Urban Computing

## 1 Introduction

There has been increased concern about spatiotemporal predictive policing that forecasts the future crime risks for each community in the urban area, since it provides the significant aids for law enforcements to better identify the underlying patterns behind the crime propagations, efficiently deploy the limited police resources and improve the public safety [3]. However, the task of forecasting where and when the crimes will occur is inherently difficult because it is sensitive to the highly complex distributions of crimes in space and time. Whereas, recent literature recognized that crime incidents tend to exhibit spatial and temporal dependencies with the dynamical social environments [1] [2]. The spatial

dependencies denote the crime risks of a region are affected by the crime-related events or environment factors in its spatial proximate regions as well as distant regions. For example, empirical evidence identified that burglary offenders, bars, incomes, race populations [4] and traffics [13] were statistically related to the spatial concentration of crime. On the other side, the temporal dependencies mean the crime risks of a region are influenced by the crime-related events or environment factors at recent, near and even distant time intervals. For example, the near-repeated patterns found in crimes indicated the recent frequently crimes are considered to be the powerful variable for predicting local crime risks in the immediate future [4]. Moreover, dynamical social events such as 311 or 911 incidents, may imply high crime risks in the near spatiotemporal scope [8]. In summary, the challenge in crime prediction centered on identifying the effective spatiotemporal dependencies from the dynamic interplay of crimes between space, time and environmental factors.

In order to address this challenge, scholars have incorporated spatiotemporal point processes [9] and random space-time distribution hypothesis [10] for crime predictions by modeling the crime spatial propagations. The risk terrain analysis [11], geography regressive models and Bayesian models [12] were also developed to assess how multiple environment factors contribute to future crime risks. Taking the dynamical correlations between crimes and other social activities into consideration, recently studies have explored various feature engineering approaches to characterize the crime-related features regarding Foursquare data [6], Twitter data [7], 911 events [8] and taxi trajectories [13], for enhancing the predictive power. However, most of the studies required profound crime knowledge and resorted to complicated spatiotemporal analysis or cumbersome feature engineering processes. Furthermore, once a bit of data changed, many features must be re-analysis and re-engineered by hand again. Thus, it is not only a challenging to capture valid